A. Appendix: Proofs

The proofs of Theorem 1-3 are along the lines of Wied and Galeano (2013).

Proof of Theorem 1

Let $D[d_1, d_2]$ be the space of càdlàg functions on the interval $[d_1, d_2]$ equipped with the supremum norm. Denote the time invariant vector of variances by $\sigma^2 = \left(\sigma_1^2, \ldots, \sigma_p^2\right)'$ and define $\{P_m(d),\ d \in [c, B]\}$ by

$$P_m(d) = \hat{D}^{-\frac{1}{2}} \frac{[m \cdot d] - [m \cdot c]}{\sqrt{m}} \left(\left[\hat{\sigma}^2\right]_{[m \cdot c]}^{[m \cdot d]} - \sigma^2\right) = \hat{D}^{-\frac{1}{2}} \frac{[m \cdot d] - [m \cdot c]}{\sqrt{m}} \begin{pmatrix} \left[\hat{\sigma}_1^2\right]_{[m \cdot c]}^{[m \cdot d]} - \sigma_1^2 \\ \vdots \\ \left[\hat{\sigma}_p^2\right]_{[m \cdot c]}^{[m \cdot d]} - \sigma_p^2 \end{pmatrix}.$$

To obtain convergence on $D[c, B]$, we use the invariance principle of Theorem 29.18 in Davidson (1994) and argue analogously to Lemma A.1 in Wied et al. (2012b). For fixed $c \geq 0$ and assuming $m \to \infty$, $\{P_m(d),\ d \in [c, B]\}$ converges in distribution to $\{W_p(d) - W_p(c),\ d \in [c, B]\}$ with $W_p(\cdot)$ being a p dimensional Brownian Motion.

$$S_m(b) := \begin{pmatrix} \hat{D}^{-\frac{1}{2}} \frac{[m \cdot b]+2}{\sqrt{m}} \left(\left[\hat{\sigma}^2\right]_{m+1}^{m+[m \cdot b]+2} - \sigma^2\right) \\ \hat{D}^{-\frac{1}{2}} \sqrt{m} \left(\left[\hat{\sigma}^2\right]_1^m - \sigma^2\right) \end{pmatrix} \Rightarrow_d \begin{pmatrix} W_p(b+1) - W_p(1) \\ W_p(1) \end{pmatrix}, \text{ for } b \in [0, B].$$

Consequently,

$$V_{[m \cdot b]+2} = \hat{D}^{-\frac{1}{2}} \frac{[m \cdot b] + 2}{\sqrt{m}} \left(\left[\hat{\sigma}^2\right]_{m+1}^{m+[m \cdot b]+2} - \sigma^2\right) - \hat{D}^{-\frac{1}{2}} \frac{[m \cdot b] + 2}{\sqrt{m}} \left(\left[\hat{\sigma}^2\right]_1^m - \sigma^2\right)$$

converges to the process $\{W_p(b+1) - (b+1)W_p(1),\ b \in [0, B]\}$. Applying the continuous mapping theorem and calculating the covariance structure of the limit process proves the result. ■

Proof of Theorem 2

The proof uses the same arguments as the one of Theorem 1 and is mainly based on the fact that for fixed $c \geq 0$, and $m \to \infty$ the process $\{P_m(d),\ d \in [c, B]\}$ converges in distribution to

$$\left\{ W_p(d) - W_p(c) + H \begin{pmatrix} \int_c^d g_1(z)dz \\ \vdots \\ \int_c^d g_p(z)dz \end{pmatrix},\ d \in [c, B] \right\}$$

on $D[c, B]$. The constant H is, up to a constant, the limit of $\hat{D}$ under the null hypothesis, see the proof of Theorem 2 in Wied et al. (2012a). This result is a generalization of arguments used in Theorem 2 in Wied et al. (2012a), executed along the lines of to the proof of Theorem 1. ■

Proof of Theorem 3

Assume w.l.o.g. $g_1(\cdot) := Mh(\cdot)$. Then, the detector converges in the following way:

$$\sup_{b \in [0,B]} \left\| V_{\lfloor mb \rfloor + 2} \right\|_2 \overset{d}{\Rightarrow} \sup_{b \in [0,B]} \left\| \begin{pmatrix} G_1(b) \\ \vdots \\ G_p(b) \end{pmatrix} + D^{-\frac{1}{2}} \begin{pmatrix} M \cdot \int_1^{b+1} h(u)du \\ \int_1^{b+1} g_2(u)du \\ \vdots \\ \int_1^{b+1} g_p(u)du \end{pmatrix} \right\|_2 . \tag{1}$$

Denote $D^{-\frac{1}{2}} := \left(d_{ij}\right)_{i,j=1,\ldots,p}$ and define constants $c_1(b) := \int_1^{b+1} h(u)du$ and $c_i(b) := \int_1^{b+1} g_i(u)du$, $i = 2, \ldots, p$. Thus, (1) has asymptotically the same distribution as

$$\sup_{b \in [0,B]} \sqrt{\sum_{j=1}^{p} \left(G_j(b) + Md_{j1}c_1(b) + \sum_{i=2}^{p} d_{ji}c_i(b) \right)^2 }. \tag{2}$$

Since D_p is positive definite there exists $j \in \{1, \ldots, p\}$ with $d_{j1} \neq 0$. Assuming $M \to \infty$, we have $\left| G_j(b) + Md_{j1}c_1(b) \right| \overset{p}{\to} \infty$. Thus, Jensen's inequality implies that for all $b \in (0, B]$ the square root of the sum in (2) tends to ∞. The fact that the term degenerates for $b = 0$ does not affect this result, since this event occurs with zero probability. This implies that (2) will exceed every quantile of the asymptotic null distribution for $M \to \infty$. ■

Proof of Lemma 1

Hafner (2003) provides conditions to establish the existence of the matrix of fourth moments and cross moments of a multivariate $GARCH(1,1)$ model in *vech* representation:

$$vech\left(H_t\right) = C_0 + A_1 vech\left(X_{t-1}X_{t-1}'\right) + B_1 vech\left(H_{t-1}\right), \tag{3}$$

where C_0 is a d dimensional parameter vector and A_1 and B_1 are parameter matrices of dimension $d \times d$. The closely related *vec* representation is given as

$$vec\left(H_t\right) = C_0^* + A_1^* vec\left(X_{t-1}X_{t-1}'\right) + B_1^* vec\left(H_{t-1}\right) \tag{4}$$

and contains several redundant equations that lead to inflated parameter matrices A_1^* and B_1^* of dimension $p^2 \times p^2$ and a parameter vector C_0^* of dimension p^2. Following Engle and Kroner (1995), the model in (7) in the main paper can be given in *vec* representation by choosing

$$C_0^* = (1-\alpha-\beta)\left[H^{\frac{1}{2}} \otimes H^{\frac{1}{2}}\right] vec\left(I_p\right), \quad A_1^* = \alpha I_{p^2} \quad \text{and} \quad B_1^* = \beta I_{p^2}. \tag{5}$$

in (4). Thus, (7) can be given in *vech* representation by transforming it first to its *vec* and then to its *vech* representation. Substituting (5) in (4) and multiplying D_p and L_p gives

$$C_0 = (1-\alpha-\beta) L_p \cdot H^{\frac{1}{2}} \otimes H^{\frac{1}{2}} \cdot vec\left(I_p\right), \quad A_1 = \alpha I_d \quad \text{and} \quad B_1 = \beta I_d \tag{6}$$

in model (3). Note that $A_1 \otimes A_1 = \alpha^2 I_{d^2}$, $B_1 \otimes B_1 = \beta^2 I_{d^2}$ and $A_1 \otimes B_1 = B_1 \otimes A_1 = \alpha\beta I_{d^2}$. Using (6) and G_p from Hafner (2003) to construct Z allows to check the existence of Γ according to Hafner (2003). ■

B. Appendix: Further Simulations: Monitoring Time Series of I.I.D. Random Vectors

To begin with, we investigate the size of the proposed procedure under the null hypothesis of no structural break. First, we simulate time series that capture neither serial nor cross-sectional dependence to gain reference values to which the performance in more complex scenarios can be compared. As simplest possible case, realizations of processes of i.i.d. random vectors are simulated. These simulation results can work as a benchmark for more complex simulation scenarios. The random vectors under consideration are i.i.d. multivariate normal and multivariate t distributed with $\nu = 8$ degrees of freedom. As covariance matrix the matrices

$$\Sigma_2 = \begin{pmatrix} 1 & 0.7 \\ 0.7 & 1 \end{pmatrix}, \ \Sigma_5 = \begin{pmatrix} 1 & 0.3 & 0.4 & 0.5 & 0.6 \\ 0.3 & 1 & 0.3 & 0.4 & 0.5 \\ 0.4 & 0.3 & 1 & 0.3 & 0.4 \\ 0.5 & 0.4 & 0.3 & 1 & 0.3 \\ 0.6 & 0.5 & 0.4 & 0.3 & 1 \end{pmatrix} \text{ and } \Sigma_{10} = \begin{pmatrix} 1 & 0.1 & 0.11 & 0.12 & 0.15 & 0.2 & 0.25 & 0.3 & 0.35 & 0.4 \\ 0.1 & 1 & 0.1 & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & 0.35 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0.35 & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & 0.1 & 1 & 0.1 \\ 0.4 & 0.35 & 0.3 & 0.25 & 0.2 & 0.15 & 0.12 & 0.11 & 0.1 & 1 \end{pmatrix}$$

are used as well as identity matrices I_p of corresponding dimension p. To enable a reasonable comparison of the results, the covariance matrices in the case of the t distribution are standardized by multiplying $\frac{\nu-2}{\nu}$. The results are given in Tables 4 and 5 in Appendix B and illustrated in Figure 1. For the sake of clarity and since the results differ only slightly for the different values of the tuning parameter γ and the different types of covariance matrix, the figure only shows the empirical sizes for $\gamma = 0$ and an identity covariance matrix.

The fact that there is hardly a difference in the empirical sizes depending on whether the covariance matrix is diagonal or not was expected as our procedure is only based on estimates of the main diagonal elements of the covariance matrix and not of the remaining entries. In general, the empirical size increases with the dimension. In order to determine the source of this, we use the actual matrix D_p that can be easily calculated for an identity covariance matrix I_p and its standardized analogue $\frac{\nu-2}{\nu} I_p$, respectively. The matrix is given as $D_p = 2I_p$ for normal distributed random vectors and as $D_p = \frac{2(\nu-1)}{\nu-4} I_p$ for t distributed ones. The results are also given in Tables 4 and 5 in Appendix B and illustrated in Figure 1. They state that the main fraction of

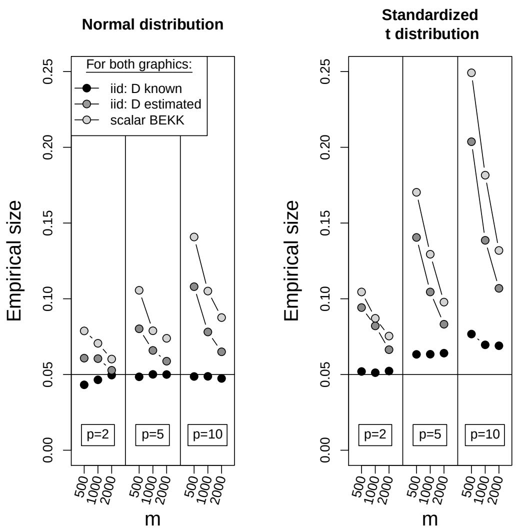

Figure 1: Size comparison: i.i.d. random vectors with matrix D_p known and estimated, respectively, and scalar $BEKK$ time series.

the increased size is caused by an insufficient estimation of the matrix D_p. Furthermore, heavy tails in the distribution of the random vectors entail an additional size increase. Unfortunately, the estimation of the matrix D_p could not be improved by using an alternative bandwidth or estimation procedure. The empirical size is distinctly larger in the case of the t distributed random vectors and decreases with growing length of the historical period m. This convergence to the theoretical size goes back to the fact that all of the asymptotic statements are established for $m \to \infty$. While for the different values of B - indicating different lengths of the monitoring period - no tendency in the empirical sizes can be recognized, larger values of γ result in a slight increase of the sizes. This is a plausible result as larger values of this parameter tend to sensitize the procedure for changes that are expected early in the monitoring period at the expense of increased probabilities of false alarms.

In the following, the power of the monitoring procedure is investigated considering two different types of scenario. In both cases the covariance matrix in the pre-break period equates the matrix Σ_p whose diagonal elements are affected by a structural break later in the series. In the first setting, the variances of all components increase from 1 to 1.3. In the second one, the variance of only one of the components jumps to 1.5. In both scenarios the power to detect an early and a later occurring change are compared. Since the length of the monitoring period depends on the parameters m and B, we assume that, independent of the length of the time series, the change happens at the same fraction of the monitoring period indicated by $\lambda^* \in (0, 1)$. We choose $\lambda^* \in \{0.05, 0.5\}$ to mark changepoints located at the beginning ($k^* = 0.05mB$) or in the middle ($k^* = 0.5mB$) of the monitoring period. The results for the first scenario are given in Tables 6 and 7 in Appendix B and illustrated in Figure 2, while those for the second scenario are presented in Tables 8 and 9 and illustrated in Figure 3. They state that the power increases considerably with growing length of the historical and the monitoring period. If all of the variances are affected by a change, the power increases with growing dimension of the random vectors. If only one of the variances experiences a change, the frequency of detecting the change decreases for growing dimension p since the portion of variance components that are not struck by the change increases. Early changes can be detected reliably in both scenarios. However, the power gets quite low if the changepoint is located in the advanced series, especially for t distributed random vectors as the rejection fractions in Tables 7 and 9 state. The direct comparison of the two scenarios shows that a major change in just one of the variances can be detected more frequently than a minor change that affects all of the variances only when

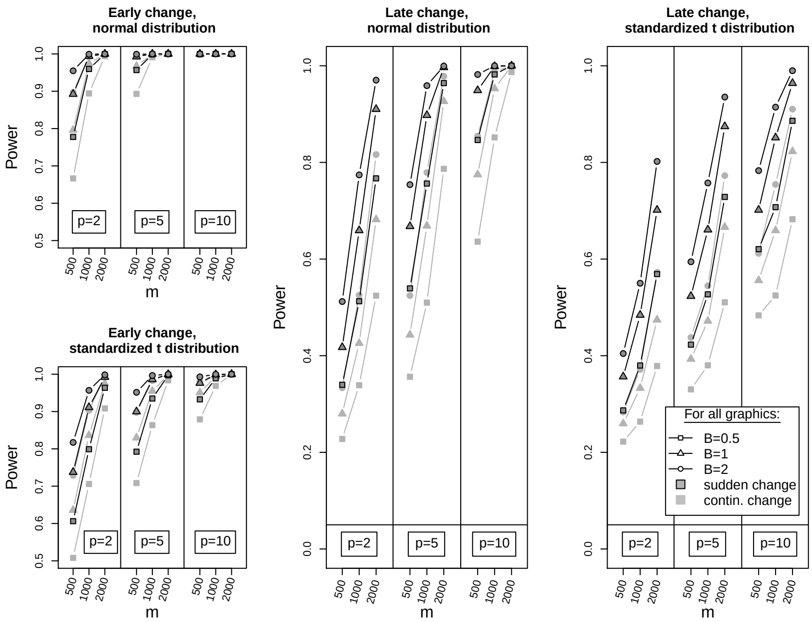

Figure 2: Power: i.i.d. random vectors when all of the variances are affected by a change.

the dimension is rather small and the change occurs not too late in the monitoring period. In all of the settings the procedure performs worse in the case of t distributed random vectors, but the differences to the normal distribution results are declining with m. Also, in most cases the power is lower for the higher value of γ. While for a later change this is a plausible result, it contradicts the expectation that early changes can be detected more frequently using a higher value of γ. An explanation for this result is that in both cases the values of the detector are compared to the values of the scaled threshold function that has a higher slope in the case of the larger tuning parameter. Since both functions intersect the down scaling of the differences by multiplying $\frac{k}{\sqrt{m}}$ can cause an earlier crossing of the threshold function for $\gamma = 0$ than for $\gamma = 0.25$. Overall, changes that occur right after the beginning of the monitoring period can be detected much more frequently than those located in the advanced monitoring period no matter how the tuning parameter was chosen.

Now, the results can be compared to scenarios of continuously appearing changes, i.e., a slow linear increase of the affected variances that starts at $\lambda_1^* = 0.05$ and 0.5, respectively, and is completed at $\lambda_2^* = 0.3$ and 0.75, respectively. The results are also illustrated in Figures 2 and 3 and presented in Tables 6-9 in Appendix B as values in parentheses. The impact of variations

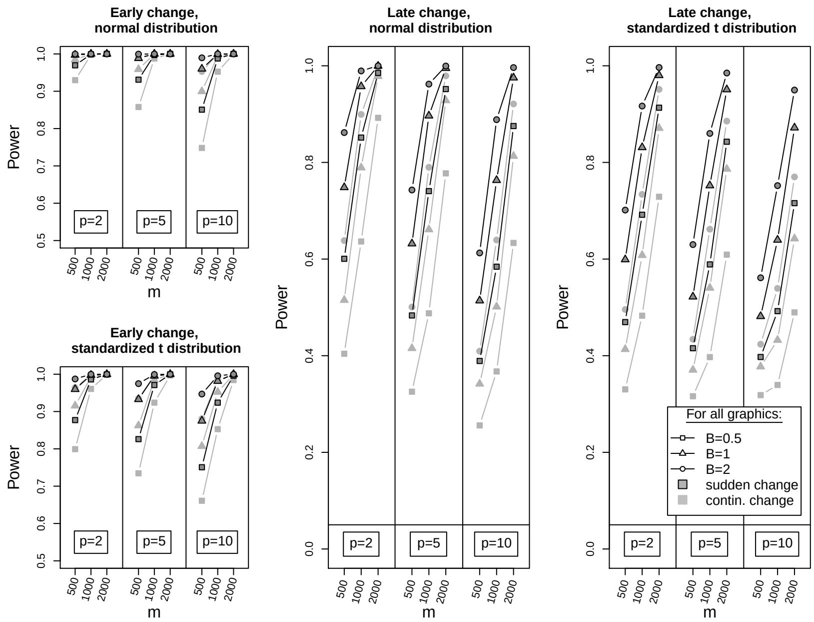

Figure 3: Power: i.i.d. random vectors when only one of the variances is affected by a change.

in the parameters remains the same as in the situation of a sudden variance change. However, the power is considerably lower in the case of a slow increase. Since the power simulations for sudden changes suggest that later changes can be detected less frequently it is clear that changes that are completed later in the monitoring period are more difficult to be detected. Although in our simulations the detectability of changes that start in the advanced monitoring period is kind of low especially for short historical periods, the power increases quickly with growing length of the historical period.

C. Appendix: Tables

	γ	B	$p=2$, $m=500$	$p=2$, 1000	$p=2$, 2000	$p=5$, $m=500$	$p=5$, 1000	$p=5$, 2000	$p=10$, $m=500$	$p=10$, 1000	$p=10$, 2000
D is known	0	0.5	0.0476	0.0431	0.0451	0.0493	0.0518	0.0535	0.0500	0.0502	0.0515
		1	0.0432	0.0465	0.0496	0.0485	0.0501	0.0500	0.0487	0.0488	0.0474
		2	0.0459	0.0435	0.0507	0.0507	0.0520	0.0536	0.0527	0.0533	0.0493
	0.25	0.5	0.0522	0.0489	0.0434	0.0550	0.0480	0.0518	0.0499	0.0496	0.0499
		1	0.0487	0.0473	0.0498	0.0470	0.0474	0.0457	0.0473	0.0485	0.0487
		2	0.0516	0.0462	0.0478	0.0528	0.0506	0.0539	0.0529	0.0522	0.0517
$\Sigma = I_p$	0	0.5	0.0659	0.0558	0.0574	0.0740	0.0641	0.0607	0.1041	0.0726	0.0652
		1	0.0608	0.0605	0.0528	0.0802	0.0659	0.0588	0.1080	0.0781	0.0650
		2	0.0689	0.0605	0.0598	0.0852	0.0657	0.0573	0.1016	0.0826	0.0628
	0.25	0.5	0.0639	0.0613	0.0545	0.0839	0.0677	0.0613	0.1034	0.0752	0.0633
		1	0.0674	0.0623	0.0573	0.0879	0.0668	0.0584	0.1144	0.0884	0.0755
		2	0.0702	0.0564	0.0539	0.0820	0.0747	0.0605	0.1132	0.0813	0.0666
$\Sigma = H_p$	0	0.5	0.0636	0.0588	0.0569	0.0788	0.0652	0.0607	0.1005	0.0741	0.0645
		1	0.0632	0.0611	0.0580	0.0845	0.0669	0.0607	0.1083	0.0814	0.0696
		2	0.0662	0.0588	0.0589	0.0844	0.0735	0.0644	0.1024	0.0787	0.0642
	0.25	0.5	0.0620	0.0672	0.0576	0.0844	0.0732	0.0646	0.1134	0.0818	0.0680
		1	0.0646	0.0570	0.0518	0.0900	0.0800	0.0652	0.1128	0.0850	0.0760
		2	0.0696	0.0640	0.0508	0.0926	0.0664	0.0688	0.1190	0.0946	0.0690

Table 4: Size when monitoring a sequence of realizations of i.i.d. $N\left(0, \Sigma_p\right)$ distributed random vectors.

	γ	B	$p=2$, $m=500$	$p=2$, 1000	$p=2$, 2000	$p=5$, $m=500$	$p=5$, 1000	$p=5$, 2000	$p=10$, $m=500$	$p=10$, 1000	$p=10$, 2000
D is known	0	0.5	0.0492	0.0509	0.0520	0.0713	0.0614	0.0610	0.0777	0.0719	0.0695
		1	0.0520	0.0512	0.0523	0.0633	0.0634	0.0641	0.0767	0.0696	0.0690
		2	0.0533	0.0526	0.0555	0.0634	0.0631	0.0639	0.0746	0.0771	0.0724
	0.25	0.5	0.0631	0.0590	0.0582	0.0831	0.0754	0.0657	0.1073	0.0911	0.0907
		1	0.0636	0.0601	0.0586	0.0810	0.0762	0.0706	0.0945	0.0912	0.0813
		2	0.0625	0.0621	0.0528	0.0845	0.0749	0.0706	0.1033	0.0914	0.0872
$\Sigma = I_p$	0	0.5	0.0914	0.0796	0.0711	0.1356	0.1066	0.0830	0.1943	0.1430	0.1053
		1	0.0942	0.0821	0.0664	0.1405	0.1045	0.0832	0.2037	0.1386	0.1069
		2	0.1027	0.0800	0.0701	0.1475	0.1085	0.0836	0.2013	0.1384	0.0961
	0.25	0.5	0.1095	0.0906	0.0775	0.1632	0.1239	0.0993	0.2329	0.1635	0.1169
		1	0.1199	0.0906	0.0815	0.1713	0.1279	0.1020	0.2487	0.1810	0.1324
		2	0.1079	0.0967	0.0738	0.1741	0.1259	0.0961	0.2490	0.1670	0.1210
$\Sigma = H_p$	0	0.5	0.0966	0.0818	0.0717	0.1382	0.1067	0.0900	0.2008	0.1382	0.1006
		1	0.1003	0.0792	0.0686	0.1413	0.1101	0.0848	0.2107	0.1459	0.1057
		2	0.0978	0.0791	0.0745	0.1413	0.1112	0.0860	0.1962	0.1405	0.1013
	0.25	0.5	0.1140	0.0918	0.0836	0.1622	0.1212	0.0924	0.2472	0.1706	0.1162
		1	0.1138	0.0878	0.0712	0.1850	0.1316	0.1026	0.2522	0.1662	0.1224
		2	0.1174	0.0918	0.0718	0.1796	0.1334	0.1036	0.2702	0.1832	0.1214

Table 5: Size when monitoring a sequence of realizations of i.i.d. $t_\nu\left(0, \frac{\nu-2}{\nu}\Sigma_p\right)$ distributed random vectors with ν=8 degrees of freedom.

			$k^* = 0.05$			$k^* = 0.5$		
	γ	B	$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.7775 (0.6665)	0.9597 (0.8941)	0.9995 (0.9938)	0.3398(0.2276)	0.5127 (0.3389)	0.7670 (0.5243)
		1	0.8923 (0.7960)	0.9939 (0.9742)	1.0000 (0.9998)	0.4174 (0.2798)	0.6592 (0.4258)	0.9101 (0.6819)
		2	0.9549 (0.8972)	0.9992 (0.9929)	1.0000 (1.0000)	0.5121 (0.3336)	0.7742 (0.5253)	0.9703 (0.8163)
	0.25	0.5	0.7664 (0.6482)	0.9552 (0.8818)	0.9995 (0.9929)	0.3137 (0.2073)	0.4846 (0.3123)	0.7483 (0.4987)
		1	0.8876 (0.7848)	0.9917 (0.9644)	1.0000 (0.9997)	0.3930 (0.2599)	0.6095 (0.3750)	0.8885 (0.6337)
		2	0.9432 (0.8689)	0.9987 (0.9901)	1.0000 (1.0000)	0.4585 (0.2890)	0.7364 (0.4771)	0.9604 (0.7841)
$p = 5$	0	0.5	0.9568 (0.8929)	0.9987 (0.9911)	1.0000 (1.0000)	0.5393 (0.3564)	0.7563 (0.5098)	0.9642 (0.7866)
		1	0.9926 (0.9671)	1.0000 (0.9997)	1.0000 (1.0000)	0.6677 (0.4431)	0.8977 (0.6687)	0.9967 (0.9264)
		2	0.9991 (0.9934)	1.0000 (1.0000)	1.0000 (1.0000)	0.7540 (0.5245)	0.9590 (0.7791)	0.9994(0.9782)
	0.25	0.5	0.9553 (0.8852)	0.9987 (0.9900)	1.000 (0.9999)	0.5155 (0.3344)	0.7431 (0.4934)	0.9546 (0.7501)
		1	0.9919 (0.9630)	1.0000 (0.9997)	1.0000 (1.0000)	0.6409 (0.4137)	0.8752 (0.6294)	0.9951 (0.9044)
		2	0.9990 (0.9918)	1.0000 (1.0000)	1.0000 (1.0000)	0.7286 (0.4893)	0.9508 (0.7509)	0.9994 (0.9725)
$p = 10$	0	0.5	0.9998 (0.9977)	1.0000 (1.0000)	1.0000 (1.0000)	0.8464 (0.6361)	0.9821 (0.8518)	1.0000 (0.9870)
		1	1.0000 (1.0000)	1.0000 (1.0000)	1.0000 (1.0000)	0.9491 (0.7749)	0.9989 (0.9529)	1.0000 (0.9994)
		2	1.0000 (1.0000)	1.0000 (1.0000)	1.0000 (1.0000)	0.9820 (0.8546)	1.0000 (0.9885)	1.0000 (1.0000)
	0.25	0.5	0.9997 (0.9969)	1.0000 (1.0000)	1.0000 (1.0000)	0.8270 (0.6084)	0.9736 (0.8174)	1.000 (0.9840)
		1	1.0000 (1.0000)	1.0000 (1.0000)	1.0000 (1.0000)	0.9349 (0.7433)	0.9986 (0.9434)	1.0000 (0.9994)
		2	1.0000 (1.0000)	1.0000 (1.0000)	1.0000 (1.0000)	0.9774 (0.8499)	0.9999 (0.9868)	1.0000 (1.0000)

Table 6: Power when monitoring a sequence of realizations of i.i.d. $N\left(0, \Sigma_p\right)$ distributed random vectors when all of the variances are affected by a change.

			$k^* = 0.05$			$k^* = 0.5$		
	γ	B	$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.6063 (0.5079)	0.7991 (0.7059)	0.9636 (0.9083)	0.2868 (0.2222)	0.3797 (0.2635)	0.5689 (0.3786)
		1	0.7377 (0.6359)	0.9112 (0.8363)	0.9921 (0.9746)	0.3566 (0.2595)	0.4842 (0.3329)	0.7015 (0.4742)
		2	0.8173 (0.7291)	0.9568 (0.9032)	0.9984 (0.9933)	0.4045 (0.2834)	0.5500 (0.3715)	0.8021 (0.5726)
	0.25	0.5	0.6154 (0.5066)	0.7883 (0.6833)	0.9547 (0.8912)	0.2821 (0.2216)	0.3584 (0.2454)	0.5247 (0.3401)
		1	0.7339 (0.6217)	0.8980 (0.8100)	0.9902 (0.9670)	0.3479 (0.2564)	0.4371 (0.2967)	0.6646 (0.4337)
		2	0.8026 (0.7045)	0.9513 (0.8896)	0.9980 (0.9916)	0.3775 (0.2677)	0.5176 (0.3450)	0.7730 (0.5302)
$p = 5$	0	0.5	0.7924 (0.7084)	0.9349 (0.8636)	0.9971 (0.9836)	0.4229 (0.3303)	0.5270 (0.3801)	0.7286 (0.5106)
		1	0.8999 (0.8297)	0.9860 (0.9547)	0.9996 (0.9981)	0.5232 (0.3931)	0.6607 (0.4719)	0.8745 (0.6661)
		2	0.9515 (0.8975)	0.9965 (0.9827)	1.0000 (0.9996)	0.5944 (0.4377)	0.7575 (0.5446)	0.9353 (0.7727)
	0.25	0.5	0.8056 (0.7119)	0.9358 (0.8603)	0.9962 (0.9803)	0.4245 (0.3355)	0.5147 (0.3700)	0.7008 (0.4799)
		1	0.8995 (0.8250)	0.9841 (0.9503)	0.9996 (0.9977)	0.5094 (0.3898)	0.6412 (0.4536)	0.8501 (0.6338)
		2	0.9493 (0.8881)	0.9963 (0.9807)	1.0000 (0.9995)	0.5757 (0.4201)	0.7412 (0.5294)	0.9227 (0.7483)
$p = 10$	0	0.5	0.9326 (0.8790)	0.9889 (0.9687)	0.9999 (0.9990)	0.6205 (0.4834)	0.7074 (0.5246)	0.8861 (0.6824)
		1	0.9763 (0.9506)	0.9989 (0.9939)	1.0000 (1.000)	0.7016 (0.5559)	0.8513 (0.6592)	0.9639 (0.8228)
		2	0.9929(0.9806)	0.9999 (0.9990)	1.0000 (1.0000)	0.7831 (0.6117)	0.9144 (0.7545)	0.9899 (0.9103)
	0.25	0.5	0.9355 (0.8776)	0.9879 (0.9651)	0.9999 (0.9988)	0.6117 (0.4798)	0.6832 (0.4983)	0.8769 (0.6645)
		1	0.9781 (0.9510)	0.9990 (0.9919)	1.0000 (1.0000)	0.6956 (0.5564)	0.8293 (0.6292)	0.9581 (0.8033)
		2	0.9951 (0.9771)	0.9999 (0.9986)	1.0000 (1.0000)	0.7683 (0.6135)	0.8965 (0.7175)	0.9907 (0.8983)

Table 7: Power when monitoring a sequence of realizations of i.i.d. $t_\nu\left(0, \frac{\nu-2}{\nu}\Sigma_p\right)$ distributed random vectors with ν=8 degrees of freedom when all of the variances are affected by a change.

	γ	B	$k^* = 0.05$			$k^* = 0.5$		
			$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.9695 (0.9298)	0.9991 (0.9975)	1.0000 (1.0000)	0.6006 (0.4040)	0.8514 (0.6364)	0.9853 (0.8923)
		1	0.9972 (0.9843)	1.0000 (1.0000)	1.0000 (1.0000)	0.7483 (0.5150)	0.9573 (0.7892)	0.9995 (0.9784)
		2	0.9997 (0.9982)	1.0000 (1.0000)	1.0000 (1.0000)	0.8618 (0.6383)	0.9894 (0.8994)	1.0000 (0.9970)
	0.25	0.5	0.9656 (0.9196)	0.9989 (0.9967)	1.0000 (1.0000)	0.5672 (0.3673)	0.8248 (0.5966)	0.9825 (0.8792)
		1	0.9967 (0.9809)	1.0000 (1.0000)	1.0000 (1.0000)	0.7167 (0.4821)	0.9520 (0.7731)	0.9994 (0.9712)
		2	0.9997 (0.9968)	1.0000 (1.0000)	1.0000 (1.0000)	0.8280 (0.5847)	0.9861 (0.8746)	1.0000 (0.9953)
$p = 5$	0	0.5	0.9310 (0.8578)	0.9972 (0.9877)	1.0000 (0.9996)	0.4833 (0.3255)	0.7406 (0.4878)	0.9518 (0.7774)
		1	0.9883 (0.9588)	1.0000 (0.9997)	1.0000 (1.0000)	0.6319 (0.4153)	0.8966 (0.6611)	0.9950 (0.9283)
		2	0.9995 (0.9908)	1.0000 (1.0000)	1.0000 (1.0000)	0.7430 (0.5007)	0.9621 (0.7900)	0.9995 (0.9792)
	0.25	0.5	0.9244 (0.8443)	0.9968 (0.9853)	1.0000 (0.9996)	0.4566 (0.2945)	0.7144 (0.4595)	0.9444 (0.7568)
		1	0.9874 (0.9533)	1.0000(0.9996)	1.0000 (1.0000)	0.6135 (0.3952)	0.8707 (0.6152)	0.9936 (0.9140)
		2	0.9988 (0.9890)	1.0000 (1.0000)	1.0000 (1.0000)	0.7191 (0.4722)	0.9530 (0.7582)	0.9994 (0.9720)
$p = 10$	0	0.5	0.8507 (0.7481)	0.9878 (0.9524)	1.0000 (0.9996)	0.3891 (0.2557)	0.5842 (0.3674)	0.8753 (0.6334)
		1	0.9600 (0.8996)	0.9993 (0.9941)	1.0000 (1.0000)	0.5139 (0.3417)	0.7631 (0.5013)	0.9753 (0.8131)
		2	0.9896 (0.9530)	1.0000 (0.9996)	1.0000 (1.0000)	0.6127 (0.4093)	0.8885 (0.6395)	0.9963 (0.9210)
	0.25	0.5	0.8541 (0.7444)	0.9879 (0.9504)	1.0000 (0.9996)	0.3814 (0.2543)	0.5727 (0.3550)	0.8574 (0.5955)
		1	0.9575 (0.8892)	0.9993 (0.9934)	1.0000 (1.0000)	0.4898 (0.3244)	0.7453 (0.4769)	0.9702 (0.7898)
		2	0.9886 (0.9477)	1.0000 (0.9995)	1.0000 (1.0000)	0.5843 (0.3821)	0.8730 (0.6110)	0.9950 (0.9082)

Table 8: Power when monitoring a sequence of realizations of i.i.d. $N\left(0, \Sigma_p\right)$ distributed random vectors when only one of the variances is affected by a change.

	γ	B	$k^* = 0.05$			$k^* = 0.5$		
			$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.8771 (0.7992)	0.9861 (0.9606)	0.9994 (0.9989)	0.4695 (0.3303)	0.6917 (0.4828)	0.9132 (0.7289)
		1	0.9597 (0.9155)	0.9976 (0.9921)	0.9998 (0.9997)	0.5990 (0.4133)	0.8311 (0.6079)	0.9802 (0.8709)
		2	0.9873 (0.9641)	0.9998 (0.9976)	0.9999 (0.9999)	0.7014 (0.4957)	0.9167 (0.7339)	0.9965 (0.9512)
	0.25	0.5	0.8717 (0.7878)	0.9836 (0.9544)	0.9993 (0.9986)	0.4522 (0.3206)	0.6599 (0.4538)	0.8969 (0.6931)
		1	0.9564 (0.9064)	0.9972 (0.9904)	0.9998 (0.9997)	0.5784 (0.3974)	0.8124 (0.5769)	0.9731 (0.8427)
		2	0.9848 (0.9551)	0.9995 (0.9972)	0.9999 (0.9998)	0.6687 (0.4624)	0.9015 (0.7018)	0.9945 (0.9395)
$p = 5$	0	0.5	0.8261 (0.7345)	0.9710 (0.9238)	0.9995 (0.9968)	0.4155 (0.3161)	0.5889 (0.3971)	0.8428 (0.6091)
		1	0.9327 (0.8623)	0.9955 (0.9846)	0.9999 (0.9997)	0.5220 (0.3706)	0.7521 (0.5402)	0.9508 (0.7864)
		2	0.9748 (0.9352)	0.9993 (0.9958)	0.9999 (0.9998)	0.6300 (0.4340)	0.8600 (0.6618)	0.9851 (0.8855)
	0.25	0.5	0.8295 (0.7370)	0.9686 (0.9165)	0.9996 (0.9961)	0.4205 (0.3272)	0.5665 (0.3805)	0.8277 (0.5871)
		1	0.9307 (0.8552)	0.9947 (0.9801)	0.9999 (0.9997)	0.5102 (0.3687)	0.7196 (0.5018)	0.9423 (0.7646)
		2	0.9728 (0.9267)	0.9993 (0.9950)	0.9999 (0.9998)	0.6135 (0.4242)	0.8380 (0.6273)	0.9832 (0.8746)
$p = 10$	0	0.5	0.7508 (0.6610)	0.9238 (0.8528)	0.9961 (0.9843)	0.3973 (0.3184)	0.4922 (0.3394)	0.7157 (0.4896)
		1	0.875 (0.8071)	0.9815 (0.9522)	0.9998 (0.9989)	0.4815 (0.3773)	0.6395 (0.4323)	0.8718 (0.6423)
		2	0.9469 (0.8809)	0.9958 (0.9849)	1.0000 (0.9994)	0.5613 (0.4238)	0.7520 (0.5393)	0.9498 (0.7700)
	0.25	0.5	0.7605 (0.6705)	0.9207 (0.8456)	0.9954 (0.9806)	0.4150 (0.3410)	0.4838 (0.3398)	0.6851 (0.4607)
		1	0.8764 (0.8014)	0.9819 (0.9512)	0.9998 (0.9983)	0.4830 (0.3883)	0.6348 (0.4341)	0.8552 (0.6176)
		2	0.9462 (0.8787)	0.9950 (0.9822)	1.0000 (0.9993)	0.5660 (0.4325)	0.7358 (0.5250)	0.9416 (0.7451)

Table 9: Power when monitoring a sequence of realizations of i.i.d. $t_\nu\left(0, \frac{\nu-2}{\nu}\Sigma_p\right)$ distributed random vectors with ν=8 degrees of freedom when only one of the variances is affected by a change.

			p = 2			p = 5			p = 10		
	γ	B	$m = 500$	1000	2000	$m = 500$	1000	2000	$m = 500$	1000	2000
multivariate procedure	0	0.5	0.0733	0.0694	0.0612	0.0984	0.0778	0.0662	0.1325	0.1031	0.0834
		1	0.0788	0.0706	0.0602	0.1056	0.0789	0.0739	0.1408	0.1051	0.0876
		2	0.0762	0.0716	0.0692	0.1058	0.0861	0.0723	0.1326	0.0973	0.0785
	0.25	0.5	0.0751	0.0704	0.0578	0.1103	0.0822	0.0734	0.1362	0.0987	0.0798
		1	0.0879	0.0693	0.0666	0.1147	0.0888	0.0787	0.1540	0.1128	0.0925
		2	0.0836	0.0694	0.0596	0.1149	0.0810	0.0731	0.1477	0.1113	0.0908
univariate procedures	0	0.5	0.0645	0.0596	0.0524	0.0912	0.0789	0.0683	0.1031	0.0812	0.0682
		1	0.0705	0.0634	0.0607	0.0905	0.0803	0.0694	0.1101	0.0897	0.0733
		2	0.0653	0.0602	0.0504	0.0961	0.0759	0.0738	0.0953	0.0732	0.0639
	0.25	0.5	0.0706	0.0624	0.0555	0.1065	0.0884	0.0757	0.1226	0.0884	0.0699
		1	0.0753	0.0701	0.0567	0.1001	0.0767	0.0687	0.1306	0.0992	0.0852
		2	0.0844	0.0743	0.0644	0.1048	0.0860	0.0689	0.1428	0.1068	0.0870

Table 10: Size when monitoring scalar $BEKK$ time series with parameters $\alpha = 0.03$, $\beta = 0.45$ and $N\left(0, \Sigma_p\right)$ distributed innovations.

			p = 2			p = 5			p = 10		
	γ	B	$m = 500$	1000	2000	$m = 500$	1000	2000	$m = 500$	1000	2000
multivariate procedure	0	0.5	0.1091	0.0877	0.0798	0.1533	0.1207	0.0987	0.2430	0.1674	0.1288
		1	0.1045	0.0871	0.0754	0.1703	0.1294	0.0978	0.2492	0.1816	0.1319
		2	0.1133	0.0938	0.0747	0.1684	0.1323	0.1001	0.2434	0.1663	0.1194
	0.25	0.5	0.1278	0.1005	0.0831	0.2012	0.1462	0.1173	0.2771	0.1974	0.1417
		1	0.1336	0.1082	0.0894	0.2101	0.1567	0.1091	0.3112	0.2143	0.1568
		2	0.1361	0.1018	0.0862	0.2017	0.1540	0.1160	0.3068	0.2131	0.1525
univariate procedures	0	0.5	0.0910	0.0713	0.0663	0.1443	0.1163	0.0924	0.1825	0.1369	0.1060
		1	0.1004	0.0812	0.0700	0.1448	0.1144	0.0896	0.2025	0.1468	0.1158
		2	0.0988	0.0853	0.0661	0.1508	0.1217	0.0895	0.1941	0.1369	0.1079
	0.25	0.5	0.1069	0.0919	0.0785	0.1761	0.1475	0.1107	0.2785	0.2102	0.1589
		1	0.1199	0.1022	0.0825	0.1769	0.1392	0.1046	0.2782	0.2147	0.1570
		2	0.1237	0.1015	0.0842	0.1932	0.1481	0.1157	0.2714	0.1964	0.1417

Table 11: Size when monitoring scalar $BEKK$ time series with parameters $\alpha = 0.03$, $\beta = 0.45$ and $t_\nu\left(0, \frac{\nu-2}{\nu}\Sigma_p\right)$ distributed innovations with ν=8 degrees of freedom.

			$k^* = 0.05$			$k^* = 0.5$		
	γ	B	$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.7516 (0.6546)	0.9384 (0.8732)	0.9982 (0.9900)	0.3388 (0.2451)	0.4866 (0.3405)	0.7274 (0.5131)
		1	0.8748 (0.7820)	0.9908 (0.9599)	1.0000 (0.9990)	0.4066 (0.2876)	0.6120 (0.4159)	0.8716 (0.6522)
		2	0.9390 (0.8707)	0.9978 (0.9879)	1.0000 (1.0000)	0.4944 (0.3413)	0.7308 (0.5197)	0.9436 (0.7794)
	0.25	0.5	0.7500 (0.6408)	0.9312 (0.8602)	0.9972 (0.9869)	0.3172 (0.2340)	0.4578 (0.3120)	0.6946 (0.4760)
		1	0.8708 (0.7608)	0.9888 (0.9517)	1.0000 (0.9988)	0.3828 (0.2639)	0.5762 (0.3816)	0.8522 (0.6150)
		2	0.9274 (0.8518)	0.9978 (0.9847)	1.0000 (1.0000)	0.4586 (0.3109)	0.6936 (0.4796)	0.9322 (0.7428)
$p = 5$	0	0.5	0.9416 (0.8757)	0.9974 (0.9891)	1.0000 (0.9999)	0.5108 (0.3782)	0.7194 (0.5140)	0.9412 (0.7645)
		1	0.9902 (0.9630)	1.0000 (0.9992)	1.0000 (1.0000)	0.6532 (0.4592)	0.8756 (0.6433)	0.9904 (0.9010)
		2	0.9978 (0.9878)	1.0000 (1.0000)	1.0000 (1.0000)	0.7626 (0.5333)	0.9464 (0.7625)	0.9990 (0.9622)
	0.25	0.5	0.9402 (0.8654)	0.9968 (0.9869)	1.0000 (0.9999)	0.4838 (0.3544)	0.6826 (0.4795)	0.9248 (0.7298)
		1	0.9900 (0.9586)	1.0000 (0.9991)	1.0000 (1.0000)	0.6250 (0.4360)	0.8610 (0.6146)	0.9884 (0.8840)
		2	0.9970 (0.9852)	1.0000 (1.0000)	1.0000 (1.0000)	0.7284 (0.5008)	0.9314 (0.7305)	0.9986 (0.9536)
$p = 10$	0	0.5	0.9996 (0.9964)	1.0000 (1.0000)	1.0000 (1.0000)	0.8292 (0.6333)	0.9688 (0.8231)	0.9998 (0.9795)
		1	0.9998 (0.9999)	1.0000 (1.0000)	1.0000 (1.0000)	0.9344 (0.7639)	0.9968 (0.9412)	1.0000 (0.9990)
		2	1.0000 (1.0000)	1.0000 (1.0000)	1.0000 (1.0000)	0.9786 (0.8492)	0.9996 (0.9802)	1.0000 (1.0000)
	0.25	0.5	0.9996 (0.9957)	1.0000 (1.0000)	1.0000 (1.0000)	0.8106 (0.6086)	0.9624 (0.8032)	0.9998 (0.9743)
		1	0.9998 (0.9999)	1.0000 (1.0000)	1.0000 (1.0000)	0.9234 (0.7415)	0.9962 (0.9288)	1.0000 (0.9983)
		2	1.0000 (1.0000)	1.0000 (1.0000)	1.0000 (1.0000)	0.9734 (0.8321)	0.9996 (0.9765)	1.0000 (1.0000)

Table 12: Power when monitoring scalar $BEKK$ time series and all of the variances increase ($N\left(0, \Sigma_p\right)$ distributed innovations).

	γ	B	$k^* = 0.05$			$k^* = 0.5$		
			$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.5999 (0.5036)	0.7869 (0.6778)	0.9509 (0.8787)	0.3110 (0.2225)	0.3778 (0.2525)	0.5388 (0.3506)
		1	0.7255 (0.6175)	0.8954 (0.8044)	0.9885 (0.9580)	0.3634 (0.2602)	0.4692 (0.3140)	0.6691 (0.4451)
		2	0.8115 (0.7052)	0.9474 (0.8835)	0.9973 (0.9881)	0.4022 (0.2922)	0.5604 (0.3749)	0.7846 (0.5585)
	0.25	0.5	0.6115 (0.5168)	0.7820 (0.6812)	0.9462 (0.8763)	0.3078 (0.2418)	0.3609 (0.2598)	0.5063 (0.3347)
		1	0.7241 (0.6213)	0.8873 (0.7956)	0.9858 (0.9558)	0.3517 (0.2743)	0.4434 (0.3116)	0.6342 (0.4272)
		2	0.8035 (0.6948)	0.9412 (0.8755)	0.9966 (0.9847)	0.3815 (0.2835)	0.5256 (0.3575)	0.7514 (0.5266)
$p = 5$	0	0.5	0.7884 (0.7018)	0.9277 (0.8550)	0.9924 (0.9762)	0.4446 (0.3476)	0.5299 (0.3916)	0.7123 (0.5033)
		1	0.8906 (0.8171)	0.9796 (0.9466)	0.9998 (0.9971)	0.5303 (0.4188)	0.6547 (0.4707)	0.8440 (0.6412)
		2	0.9399 (0.8823)	0.9946 (0.9774)	1.0000 (0.9997)	0.5997 (0.4534)	0.7450 (0.5464)	0.9270 (0.7491)
	0.25	0.5	0.7994 (0.7103)	0.9285 (0.8517)	0.9915 (0.9716)	0.4467 (0.3645)	0.5117 (0.3797)	0.6918 (0.4745)
		1	0.8917 (0.8188)	0.9777 (0.9348)	0.9995 (0.9953)	0.5206 (0.4077)	0.6295 (0.4593)	0.8207 (0.6193)
		2	0.9402 (0.8838)	0.9942 (0.9751)	0.9999 (0.9992)	0.5874 (0.4555)	0.7219 (0.5378)	0.9138 (0.7240)
$p = 10$	0	0.5	0.9279 (0.8772)	0.9856 (0.9609)	0.9995 (0.9988)	0.6379 (0.5284)	0.7077 (0.5673)	0.8697 (0.6859)
		1	0.9784 (0.9403)	0.9979 (0.9928)	1.0000 (0.9998)	0.7284 (0.5768)	0.8357 (0.6494)	0.9590 (0.8109)
		2	0.9902 (0.9798)	0.9999 (0.9979)	1.0000 (1.0000)	0.7953 (0.6480)	0.9071 (0.7476)	0.9877 (0.9011)
	0.25	0.5	0.9328 (0.8755)	0.9852 (0.9549)	0.9996 (0.9977)	0.6318 (0.5190)	0.6924 (0.5357)	0.8549 (0.6618)
		1	0.9780 (0.9463)	0.9977 (0.9932)	1.0000 (1.0000)	0.7121 (0.5770)	0.8171 (0.6474)	0.9485 (0.7978)
		2	0.9903 (0.9730)	0.9999 (0.9981)	1.0000 (1.0000)	0.7855 (0.6399)	0.8948 (0.7114)	0.9852 (0.8835)

Table 13: Power when monitoring scalar $BEKK$ time series and all of the variances increase ($t_\nu\left(0, \frac{\nu-2}{\nu}\Sigma_p\right)$ distributed innovations with ν=8 degrees of freedom).

	γ	B	$k^* = 0.05$			$k^* = 0.5$		
			$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.9582 (0.9063)	0.9986 (0.9950)	1.0000 (1.0000)	0.5642 (0.3937)	0.8276 (0.6026)	0.9776 (0.8623)
		1	0.9938 (0.9794)	1.0000 (0.9995)	1.0000 (1.0000)	0.7120 (0.5065)	0.9364 (0.7684)	0.9990 (0.9646)
		2	0.9992 (0.9954)	1.0000 (1.0000)	1.0000 (1.0000)	0.8358 (0.6141)	0.9808 (0.8814)	1.0000 (0.9938)
	0.25	0.5	0.9552 (0.8979)	0.9986 (0.9926)	1.0000 (1.0000)	0.5410 (0.3747)	0.8000 (0.5614)	0.9728 (0.8442)
		1	0.9918 (0.9721)	1.0000 (0.9996)	1.0000 (1.0000)	0.6862 (0.4712)	0.9248 (0.7320)	0.9990 (0.9583)
		2	0.9988 (0.9948)	1.0000 (1.0000)	1.0000 (1.0000)	0.8102 (0.5855)	0.9752 (0.8482)	1.0000 (0.9906)
$p = 5$	0	0.5	0.9120 (0.8341)	0.9954 (0.9784)	1.0000 (1.0000)	0.4640 (0.3264)	0.6984 (0.4779)	0.9378 (0.7516)
		1	0.9804 (0.9454)	0.9996 (0.9985)	1.0000 (1.0000)	0.6216 (0.4172)	0.8746 (0.6438)	0.9914 (0.9058)
		2	0.9962 (0.9862)	1.0000 (1.0000)	1.0000 (1.0000)	0.7292 (0.5058)	0.9454 (0.7637)	0.9990 (0.9696)
	0.25	0.5	0.9028 (0.8256)	0.9950 (0.9760)	1.0000 (0.9999)	0.4368 (0.3021)	0.6646 (0.4463)	0.9226 (0.7299)
		1	0.9782 (0.9364)	0.9996 (0.9985)	1.0000 (1.0000)	0.5964 (0.3930)	0.8588 (0.6079)	0.9894 (0.8873)
		2	0.9960 (0.9811)	1.0000 (1.0000)	1.0000 (1.0000)	0.7004 (0.4869)	0.9330 (0.7326)	0.9986 (0.9614)
$p = 10$	0	0.5	0.8280 (0.7390)	0.9804 (0.9396)	1.0000 (0.9985)	0.3942 (0.2859)	0.5632 (0.3695)	0.8462 (0.6011)
		1	0.9480 (0.8844)	0.9990 (0.9919)	1.0000 (1.0000)	0.5062 (0.3666)	0.7442 (0.5067)	0.9612 (0.7968)
		2	0.9878 (0.9499)	1.0000 (0.9995)	1.0000 (1.0000)	0.6328 (0.4210)	0.8622 (0.6228)	0.9936 (0.8966)
	0.25	0.5	0.8266 (0.7231)	0.9772 (0.9302)	0.9998 (0.9980)	0.3790 (0.2779)	0.5384 (0.3554)	0.8232 (0.5619)
		1	0.9464 (0.8729)	0.9988 (0.9882)	1.0000 (1.0000)	0.4914 (0.3485)	0.7208 (0.4888)	0.9528 (0.7668)
		2	0.9860 (0.9483)	1.0000 (0.9982)	1.0000 (1.0000)	0.6102 (0.3947)	0.8396 (0.5893)	0.9902 (0.8758)

Table 14: Power when monitoring scalar $BEKK$ time series and just one of the variances increases ($N\left(0, \Sigma_p\right)$ distributed innovations).

			$k^* = 0.05$			$k^* = 0.5$		
	γ	B	$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.8604 (0.7823)	0.9778 (0.9444)	0.9998 (0.9982)	0.4666 (0.3340)	0.6556 (0.4609)	0.8922 (0.7014)
		1	0.9487 (0.9004)	0.9965 (0.9895)	0.9999 (0.9997)	0.5838 (0.4263)	0.8107 (0.6036)	0.9716 (0.8481)
		2	0.9842 (0.9540)	0.9988 (0.9972)	1.0000 (1.0000)	0.6880 (0.4919)	0.8969 (0.7163)	0.9913 (0.9296)
	0.25	0.5	0.8574 (0.7725)	0.9756 (0.9365)	0.9997 (0.9977)	0.4532 (0.3186)	0.6304 (0.4463)	0.8750 (0.6724)
		1	0.9458 (0.8842)	0.9960 (0.9870)	0.9999 (0.9996)	0.5645 (0.4001)	0.7889 (0.5738)	0.9643 (0.8206)
		2	0.9818 (0.9450)	0.9988 (0.9970)	1.0000 (0.9998)	0.6656 (0.4827)	0.8810 (0.6907)	0.9892 (0.9206)
$p = 5$	0	0.5	0.8043 (0.7142)	0.9612 (0.9085)	0.9989 (0.9929)	0.4229 (0.3175)	0.5673 (0.3925)	0.8130 (0.5881)
		1	0.9135 (0.8439)	0.9933 (0.9759)	0.9996 (0.9997)	0.5342 (0.3904)	0.7229 (0.5086)	0.9314 (0.7587)
		2	0.9673 (0.9233)	0.9989 (0.9946)	1.0000 (1.0000)	0.6248 (0.4487)	0.8317 (0.6239)	0.9774 (0.8684)
	0.25	0.5	0.8046 (0.7168)	0.9599 (0.8983)	0.9988 (0.9940)	0.4274 (0.3304)	0.5554 (0.3863)	0.7947 (0.5621)
		1	0.9109 (0.8507)	0.9921 (0.9773)	0.9996 (0.9994)	0.5316 (0.4003)	0.7030 (0.5138)	0.9199 (0.7378)
		2	0.9656 (0.9207)	0.9986 (0.9925)	1.0000 (0.9999)	0.6135 (0.4460)	0.8176 (0.5954)	0.9744 (0.8456)
$p = 10$	0	0.5	0.7439 (0.6705)	0.9084 (0.8354)	0.9925 (0.9750)	0.4308 (0.3587)	0.4926 (0.3673)	0.7025 (0.4872)
		1	0.8722 (0.7969)	0.9784 (0.9419)	0.9996 (0.9984)	0.5129 (0.3983)	0.6390 (0.4642)	0.8607 (0.6375)
		2	0.9304 (0.8736)	0.9932 (0.9747)	1.0000 (0.9993)	0.5776 (0.4425)	0.7384 (0.5159)	0.9330 (0.7415)
	0.25	0.5	0.7505 (0.6736)	0.9033 (0.8235)	0.9915 (0.9700)	0.4482 (0.3761)	0.4862 (0.3648)	0.6792 (0.4611)
		1	0.8728 (0.7939)	0.9749 (0.9367)	0.9996 (0.9960)	0.5220 (0.4322)	0.6207 (0.4526)	0.8381 (0.6152)
		2	0.9326 (0.8691)	0.9924 (0.9741)	1.0000 (0.9993)	0.5859 (0.4655)	0.7270 (0.5185)	0.9238 (0.7241)

Table 15: Power when monitoring scalar $BEKK$ time series and just one of the variances increases ($t_\nu\left(0, \frac{\nu-2}{\nu}\Sigma_p\right)$ distributed innovations with ν=8 degrees of freedom).

			normal distribution						t distribution					
			$k^* = 0.05$			$k^* = 0.5$			$k^* = 0.05$			$k^* = 0.5$		
	γ	B	$m = 500$	1000	2000	$m = 500$	1000	2000	$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.7570	0.9416	0.9987	0.3344	0.4931	0.7526	0.5714	0.7736	0.9479	0.2615	0.3506	0.5175
		1	0.8772	0.9886	1.0000	0.4108	0.6381	0.8932	0.7161	0.8947	0.9892	0.3477	0.4684	0.6811
		2	0.9477	0.9978	1.0000	0.5164	0.7538	0.9583	0.8052	0.9508	0.9960	0.4051	0.5672	0.7915
	0.25	0.5	0.7495	0.9351	0.9984	0.3119	0.4591	0.7204	0.5846	0.7773	0.9474	0.2691	0.3455	0.5025
		1	0.8716	0.9870	1.0000	0.3797	0.5985	0.8686	0.7056	0.8849	0.9875	0.3338	0.4399	0.6480
		2	0.9404	0.9972	1.0000	0.4822	0.7214	0.9491	0.7843	0.9414	0.9952	0.3752	0.5244	0.7544
$p = 5$	0	0.5	0.9400	0.9966	1.0000	0.5042	0.7155	0.9250	0.7913	0.9293	0.9957	0.4323	0.5455	0.7252
		1	0.9850	0.9997	1.0000	0.6220	0.8525	0.9851	0.8905	0.9839	0.9992	0.5141	0.6556	0.8657
		2	0.9962	1.0000	1.0000	0.6988	0.9099	0.9960	0.9375	0.9932	1.0000	0.5767	0.7372	0.9157
	0.25	0.5	0.9385	0.9962	1.0000	0.4826	0.6860	0.9078	0.8023	0.9288	0.9952	0.4331	0.5283	0.7040
		1	0.9834	0.9995	1.0000	0.5850	0.8201	0.9799	0.8859	0.9820	0.9989	0.4984	0.6240	0.8391
		2	0.9955	1.0000	1.0000	0.6542	0.8836	0.9942	0.9334	0.9925	0.9999	0.5514	0.7052	0.8952
$p = 10$	0	0.5	0.9953	1.0000	1.0000	0.7139	0.8957	0.9934	0.9227	0.9872	0.9999	0.6011	0.7131	0.8720
		1	0.9996	1.0000	1.0000	0.7678	0.9476	0.9990	0.9599	0.9977	1.0000	0.6367	0.7810	0.9346
		2	1.0000	1.0000	1.0000	0.8812	0.9903	0.9999	0.9895	0.9999	1.0000	0.7353	0.8737	0.9812
	0.25	0.5	0.9947	1.0000	1.0000	0.6850	0.8697	0.9896	0.9223	0.9868	0.9996	0.5964	0.6914	0.8481
		1	0.9993	1.0000	1.0000	0.7346	0.9293	0.9988	0.9620	0.9973	1.0000	0.6287	0.7620	0.9199
		2	1.0000	1.0000	1.0000	0.8425	0.9802	0.9999	0.9888	0.9997	1.0000	0.7054	0.8446	0.9732

Table 16: Power when using univariate monitoring procedures: scalar $BEKK$ time series and all of the variances increase.

			normal distribution						t distribution					
			$k^* = 0.05$			$k^* = 0.5$			$k^* = 0.05$			$k^* = 0.5$		
	γ	B	$m = 500$	1000	2000	$m = 500$	1000	2000	$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.9095	0.9958	1.0000	0.4507	0.7100	0.9453	0.7367	0.9279	0.9962	0.3457	0.5112	0.7653
		1	0.9785	1.0000	1.0000	0.6033	0.8653	0.9945	0.8710	0.9813	0.9996	0.4473	0.6616	0.8949
		2	0.9957	1.0000	1.0000	0.7160	0.9497	0.9999	0.9285	0.9932	0.9995	0.5292	0.7599	0.9532
	0.25	0.5	0.8975	0.9944	1.0000	0.4309	0.6846	0.9381	0.7297	0.9196	0.9947	0.3366	0.4876	0.7357
		1	0.9750	0.9999	1.0000	0.5588	0.8394	0.9902	0.8592	0.9770	0.9994	0.4299	0.6328	0.8790
		2	0.9955	1.0000	1.0000	0.6964	0.9356	0.9993	0.9224	0.9919	0.9995	0.5083	0.7353	0.9455
$p = 5$	0	0.5	0.8684	0.9908	1.0000	0.3904	0.6333	0.9047	0.6736	0.8966	0.9909	0.3282	0.4417	0.6878
		1	0.9695	0.9999	1.0000	0.5594	0.8340	0.9863	0.8340	0.9715	0.9978	0.4315	0.6155	0.8659
		2	0.9910	1.0000	1.0000	0.6351	0.9132	0.9980	0.8934	0.9879	0.9987	0.4846	0.6865	0.9221
	0.25	0.5	0.8554	0.9867	1.0000	0.3653	0.5873	0.8846	0.6773	0.8923	0.9898	0.3387	0.4318	0.6681
		1	0.9585	0.9994	1.0000	0.5095	0.7948	0.9796	0.8219	0.9664	0.9973	0.4203	0.5829	0.8399
		2	0.9907	0.9999	1.0000	0.6262	0.9021	0.9980	0.8898	0.9872	0.9986	0.4856	0.6712	0.9126
$p = 10$	0	0.5	0.8388	0.9879	1.0000	0.3676	0.5919	0.8820	0.6612	0.8711	0.9903	0.3401	0.4302	0.6469
		1	0.9599	0.9993	1.0000	0.5167	0.7915	0.9787	0.8167	0.9611	0.9984	0.4340	0.5860	0.8226
		2	0.9854	1.0000	1.0000	0.5763	0.8748	0.9953	0.8709	0.9800	0.9994	0.4640	0.6514	0.8976
	0.25	0.5	0.8393	0.9857	1.0000	0.3716	0.5752	0.8677	0.6824	0.8723	0.9901	0.3845	0.4463	0.6354
		1	0.9577	0.9989	1.0000	0.5168	0.7788	0.9756	0.8277	0.9602	0.9983	0.4735	0.5954	0.8143
		2	0.9838	1.0000	1.0000	0.5572	0.8563	0.9942	0.8696	0.9783	0.9993	0.4795	0.6418	0.8846

Table 17: Power when using univariate monitoring procedures: scalar $BEKK$ time series and only one of the variances increases.

			normal distribution						t distribution					
			$k^* = 0.05$			$k^* = 0.5$			$k^* = 0.05$			$k^* = 0.5$		
	γ	B	$m = 500$	1000	2000	$m = 500$	1000	2000	$m = 500$	1000	2000	$m = 500$	1000	2000
$p = 2$	0	0.5	0.7807	0.9559	0.9990	0.3618	0.5348	0.7816	0.6241	0.8071	0.9614	0.3136	0.3901	0.5716
		1	0.8966	0.9933	1.0000	0.4497	0.6823	0.9162	0.7451	0.9112	0.9931	0.3738	0.5050	0.7194
		2	0.9556	0.9994	1.0000	0.5335	0.7911	0.9715	0.8385	0.9619	0.9980	0.4442	0.6063	0.8187
	0.25	0.5	0.7766	0.9521	0.9989	0.3408	0.5036	0.7546	0.6279	0.8001	0.9563	0.3127	0.3699	0.5420
		1	0.8895	0.9910	1.0000	0.4205	0.6440	0.8970	0.7410	0.9043	0.9911	0.3607	0.4759	0.6876
		2	0.9498	0.9988	1.0000	0.4972	0.7612	0.9651	0.8313	0.9570	0.9975	0.4228	0.5738	0.7890
$p = 5$	0	0.5	0.9589	0.9994	1.0000	0.5760	0.7803	0.9645	0.8156	0.9416	0.9962	0.4771	0.5696	0.7556
		1	0.9914	0.9999	1.0000	0.7058	0.9143	0.9969	0.9115	0.9866	0.9997	0.5624	0.6920	0.8862
		2	0.9989	1.0000	1.0000	0.8065	0.9653	0.9997	0.9570	0.9969	1.0000	0.6372	0.7955	0.9505
	0.25	0.5	0.9568	0.9994	1.0000	0.5514	0.7541	0.9564	0.8212	0.9397	0.9957	0.4742	0.5493	0.7296
		1	0.9913	0.9999	1.0000	0.6816	0.8998	0.9964	0.9144	0.9861	0.9997	0.5556	0.6740	0.8684
		2	0.9986	1.0000	1.0000	0.7865	0.9581	0.9997	0.9568	0.9968	1.0000	0.6228	0.7747	0.9403
$p = 10$	0	0.5	0.9998	1.0000	1.0000	0.8720	0.9845	1.0000	0.9453	0.9906	0.9997	0.6657	0.7525	0.9024
		1	1.0000	1.0000	1.0000	0.9604	0.9994	1.0000	0.9858	0.9998	1.0000	0.7544	0.8717	0.9721
		2	1.0000	1.0000	1.0000	0.9888	1.0000	1.0000	0.9955	0.9998	1.0000	0.8266	0.9287	0.9936
	0.25	0.5	0.9997	1.0000	1.0000	0.8578	0.9814	1.0000	0.9487	0.9902	0.9997	0.6690	0.7395	0.8920
		1	1.0000	1.0000	1.0000	0.9535	0.9991	1.0000	0.9860	0.9998	1.0000	0.7472	0.8574	0.9665
		2	1.0000	1.0000	1.0000	0.9854	0.9999	1.0000	0.9958	0.9998	1.0000	0.8191	0.9190	0.9920

Table 18: Power when the variance of the innovations increases.

References

Davidson, J. (1994): *Stochastic Limit Theory*, Oxford University Press.

Engle, R. and K. Kroner (1995): “Multivariate Simultaneaous Generalized Arch,” *Econometric Theory*, 11, 122–150.

Hafner, C. (2003): “Fourth Moment Structure of Multivariate GARCH Models,” *Journal of Financial Econometrics*, 1(1), 26–54.

Wied, D., M. Arnold, N. Bissantz, and D. Ziggel (2012a): “A New Fluctuation Test for Constant Variances with Applications to Finance,” *Metrika*, 75(8), 1111–1127.

Wied, D. and P. Galeano (2013): “Monitoring Correlation Change in a Sequence of Random Variables,” *Journal of Statistical Planning and Inference*, 143(1), 186–196.

Wied, D., W. Krämer, and H. Dehling (2012b): “Testing for a Change in Correlation at an Unknown Point in Time Using an Extended Functional Delta Method,” *Econometric Theory*, 68(3), 570–589.